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Dragana Carevic

DSTO-TR-0853

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ABSTRACT

The returns from shallowly buried targets measured using Ground Penetrating Radar (GPR) are typically obscured by a strong background signal comprised of the reflections from the air-soil interface. A Kalman filter-based approach is proposed to estimate this background signal and to separate it from the target return. In the absence of the target the filter operates using a "quiescent state model" in which it computes the background estimate. A statistic based on measurement innovation is applied to detect the target position. Upon detection the state is augmented by a new component which allows for the change of the signal corresponding to the presence of the target return. The augmented state model is used until it is reverted to the quiescent model by another decision.

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Published by

DSTO Electronics and Surveillance Research Laboratory
PO Box 1500
Salisbury, South Australia, Australia 5108

Telephone: (08) 8259 5555
Facsimile: (08) 8259 6567

AR No. AR–011–042
August, 1999

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EXECUTIVE SUMMARY

Ground Penetrating Radar (GPR) has shown promise for detecting landmines with minimal or no metal content. A problem related to this technology is that the returns from shallow buried objects can be obscured by the ground return. In the scope of its countermine project DSTO is investigating signal processing techniques for improving detection of shallow-buried targets within the ground return.

This report describes a Kalman filter-based approach to target detection and clutter suppression in near surface GPR data. The detection problem is posed as the one of detecting local anomalies in the soil dielectric half-space, where the soil properties are assumed to slowly change across the half-space as a function of distance. Background estimation, target detection and target-background separation are treated as mutually related processes and are performed within an integral Kalman filter-based computational procedure. In the absence of the target the filter operates using a quiescent signal model in which it computes the background estimate. A statistic based on the measurement innovation obtained from the Kalman filter is applied to detect the target position. Upon the detection the state is augmented by new components which allow for the change in the signal corresponding to the target return.

This technique was tested using a number of targets measured in several soil environments and proved to be superior to the standard background subtraction method. Further tests are required in order to determine the effectiveness of this technique in the environments that contain a large number of false targets (clutter). Several extensions to the current method which are expected to provide an increase in the detection capability have been suggested.

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Dragana Carevic received BSc. and M.S. degrees in Electrical Engineering from Belgrade University in 1983 and 1989, respectively. From 1983 to 1991 she worked as a Research Engineer in the Electrical Engineering Institute "Nikola Tesla" in Belgrade on the development of intelligent instrumentation for signal measurement, processing and recognition. In 1996 she received a PhD degree from Curtin University in the areas of image processing and analysis. Her research interests include signal and image processing, pattern recognition and data fusion.

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1 Introduction

Impulse time-domain Ground Penetrating Radar (GPR) is capable of detecting buried targets with little or no metal content and, as such, has emerged as a promising tool for landmine detection. GPR radiates short-duration pulses of electromagnetic energy into the ground and records backscattered signatures composed of the reflections from the target dielectric surfaces (*e.g.*, top and bottom of a mine plastic casing) and internal metallic components (*e.g.*, firing pin). However, GPR signatures of shallowly buried targets such as landmines are normally obscured by a background signal (clutter) comprised of the reflections from the ground surface and the antenna crosstalk, which, is some cases, may impede detection.

As the target and the ground returns have similar spectral characteristics standard radar clutter suppression techniques can not be used for their separation [5]. A simple alternative is to apply background subtraction whereby the background signal is estimated as the mean of the unprocessed ensemble of GPR signals using either all signals in the ensemble or a spatial moving average filter to obtain a locally adaptive background estimate [4], [5]. This estimate is next subtracted from the unprocessed GPR signals in the ensemble. The resulting data is usually utilised to locate the position of a possible target which may be followed by target recognition algorithms [2]. We note that the techniques described in [4] and [5] do not take into account the target position and can use target return signals to compute background estimate, which, in some cases, may modify the distribution of the target signatures after the subtraction. By contrast, in this report background estimation, target detection and target-background separation are treated as mutually interrelated processes and are performed within an integral Kalman filter-based computational procedure. A Kalman filter approach, motivated by the variable state dimension (VSD) method described in [1], is utilized to estimate the background signal and to separate it from the target signal. In the absence of the target the filter operates using a quiescent state model in which it computes the background estimate. The target is defined as a local anomaly in the soil dielectric and is detected as an abrupt departure from the estimated background signal. A statistic based on the measurement innovation obtained by the Kalman filter is applied to detect the target position. Upon detection the state is augmented by new components which allow for the change of the signal corresponding to the target return. The augmented state model is used until it is reverted to the quiescent model by another decision.

It is assumed that the background signal is a slowly changing function of the spatial position. The magnitude of this signal at one particular depth, and for incrementally updated spatial positions, is modelled using a random walk model. Based on this model, the noisy measurements of the background signal are represented using a state space form and Kalman filter is applied to obtain the recursive state estimates. In particular, a set of Kalman filters is run on horizontal strips of GPR data which are adjacent in depth. At the spatial positions where the target is detected the state is augmented by the new state component modelled as stochastic bias. This component is used to compute the estimate of the unknown target signal which is assumed to be superimposed onto the background signal at the position of the target.

The report is organized as follows. Section 2 describes the Kalman filter-based ap-

proach to background estimation and target-background separation. Section 3 then presents our approach to target detection using measurement innovation and Section 4 explains the technique that enables adaptation of the algorithm to slow changes of the environment. The experimental results are presented in Section 5.

2 Background Estimation and Target-Background Separation Using Kalman Filter

In the process of acquiring GPR signatures the transmit and receive antennas are moved over the ground surface at approximately constant velocity v and height h so as to cross the buried target. The received backscattered signals (or traces) $u(n,k)$ are collected in fixed time intervals Δt_c where $n = 0,\ldots,N-1$ denotes the signal time samples and $k = 0,1,\ldots,$ corresponds to the position of the receive antenna, $vk\Delta t_c$. Using the additive signal model we can write:

$$u(n,k) = s^t(n,k) + s^b(n,k) + w(n,k), \qquad n = 0,\ldots,N-1 \tag{1}$$

where $s^t(n,k)$ is the target signal, $s^b(n,k)$ is the background signal (superscript t stands for "target" and b denotes "background"), and $w(n,k)$ is additive noise. If the signal $u(n,k)$ is measured over the area with no target present $s^t(n,k) = 0,\ n = 0,\ldots,N-1$.

Two-dimensional GPR plots are obtained by stacking the traces $u(n,k)$ measured at consecutive spatial positions. The horizontal axes of a plot corresponds to the antenna position and the vertical axis denotes time duration of the backscattered signal (equivalently, proportional to the depth). The plots are composed of sections of traces that contain target signal and those measured over the areas with no target present, which constitute the background signals and the goal is to detect target and segment the data into the target and the no-target areas. To enable efficient processing, GPR plots are divided into non-overlapping horizontal strips which correspond to the layers of the ground that are approximately constant in depth. Each strip is processed separately as explained bellow.

We define the measurement vector as $\mathbf{u}_p(k) = [u(pm,k), u(pm+1,k),\ldots,u((p+1)m-1,k)]^T$, where $p = 0,1,\ldots,P-1$, and $P = [N/m]$ ($[z]$ represents the largest integer $\leq z$). That is, $\mathbf{u}_p(k)$ equals the section of length m of the received GPR signal $u(n,k)$ which starts from the pm-th signal sample and $\mathbf{u}_p(k)$, $k = 0,1,\ldots,$ is a horizontal strip of GPR data of width m positioned at pm. Following the random walk model for the background-only signals, we define the quiescent state using the following linear difference state equation:

$$\mathbf{s}_p^b(k) = \mathbf{s}_p^b(k-1) + \mathbf{v}_{1p}(k) \tag{2}$$

for $p = 0,1,\ldots,P-1$, where $\mathbf{s}_p^b(k) = [s^b(pm,k), s^b(pm+1,k),\ldots,s^b((p+1)m-1,k)]^T$. The corresponding measurement equation is then

$$\mathbf{u}_p(k) = \mathbf{s}_p^b(k) + \mathbf{w}_p(k),\ \ p = 0,1,\ldots,P-1. \tag{3}$$

In the case where the target return is present in the received signal the state space representation is defined as:

$$\begin{aligned} \mathbf{s}_p^b(k) &= \mathbf{s}_p^b(k-1) & (4)\\ \mathbf{s}_p^t(k) &= \mathbf{s}_p^t(k-1) + \mathbf{b}_p(k) & (5)\\ \mathbf{b}_p(k) &= \mathbf{b}_p(k-1) + \mathbf{v}_{2p}(k) & (6) \end{aligned}$$

for $p = 0, 1, \ldots, P-1$. The state is augmented with the vector $\mathbf{s}_p^t(k) = [s^t(pm,k), s^t(pm+1,k), \ldots, s^t((p+1)m-1,k)]^T$ and a random bias $\mathbf{b}_p(k)$ which is used to account for the changes corresponding to the target signal. The background is kept constant and equal to the value estimated prior to target detection (see Eq. (3)). For the above augmented state the measurement equation is defined as:

$$\mathbf{u}_p(k) = \mathbf{s}_p^b(k) + \mathbf{s}_p^t(k) + \mathbf{w}_p(k), \;\; p = 0, 1, \ldots, P-1. \tag{7}$$

We note that $\mathbf{v}_{1p}(k)$ in (2) and $\mathbf{v}_{2p}(k)$ in (6) are the process noise vectors and $\mathbf{w}_p(k)$ in (3) and (7) is the measurement noise vector, for $p = 0, 1, \ldots, P-1$. They are all m-dimensional vectors whose components are independent identically distributed (iid) Gaussian random variables. Also, in the background-only regime the target signal $s^t(n = 0, \ldots, N-1, k)$ is zero so that

$$\mathbf{s}_p^t(k) = [0]_{m\times 1} \;\text{ for }\; p = 0, 1, \ldots, P-1. \tag{8}$$

Based on the equations (1)-(2) and (3)-(6), a set of P Kalman filters is used to compute the background and the target signal estimates from the noisy observations. In the quiescent phase the p-th state vector $\mathbf{x}_{1p} = [\mathbf{s}_p^b]$ is recursively estimated as

$$\mathbf{x}_{1p}(k) = \mathbf{A}_1\mathbf{x}_{1p}(k-1) + \mathbf{k}_{1p}(k)(\mathbf{u}_p(k) - \mathbf{H}_1\mathbf{A}_1\mathbf{x}_{1p}(k-1)) \tag{9}$$

where $\mathbf{A}_1 = \mathbf{I}$ and $\mathbf{H}_1 = \mathbf{I}$, and $\mathbf{I}$ is an identity matrix with m elements on the main diagonal. The update equations in this case, for $p = 0, 1, \ldots, P-1$, are

$$\begin{aligned} \mathbf{P}_{1p}(k|k-1) &= \mathbf{A}_1\mathbf{P}_{1p}(k-1)\mathbf{A}_1^T + \mathbf{Q}_{1p}(k) & (10)\\ \mathbf{k}_{1p}(k) &= \mathbf{P}_{1p}(k|k-1)\mathbf{H}_1^T(\mathbf{H}_1\mathbf{P}_{1p}(k|k-1)\mathbf{H}_1^T + \mathbf{R}_p)^{-1} & (11)\\ \mathbf{P}_{1p}(k) &= (\mathbf{I} - \mathbf{k}_{1p}(k)\mathbf{H}_1)\mathbf{P}_{1p}(k|k-1) & (12) \end{aligned}$$

where $\mathbf{k}_{1p}(k)$ is a Kalman gain vector, $\mathbf{P}_{1p}(k|k-1)$ is an *a priory* error covariance matrix with the dimensions $m \times m$, $\mathbf{P}_{1p}(k)$ is the updated error covariance matrix with the same dimensions, $\mathbf{Q}_{1p}(k)$ is the process noise covariance matrix and $\mathbf{R}_p = \sigma_{w_p}^2\mathbf{I}$ is the measurement noise covariance matrix. The error covariance matrix is initialized to $\mathbf{P}_{1p}(0) = [0]_{m\times m}$ and the process noise covariance matrix to $\mathbf{Q}_{1p}(0) = (\sigma_{v_{1p}}^0)^2\mathbf{I}$, where $(\sigma_{v_{1p}}^0)^2$ is the initial estimate of the variance of the process noise sequence in (1).

When the target signal is present, the augmented state vector is

$$\mathbf{x}_{2p} = [\ [\mathbf{s}_p^b]^T,\ [\mathbf{s}_p^t]^T,\ [\mathbf{b}_p]^T]^T \tag{13}$$

and its updated estimate is

$$\mathbf{x}_{2p}(k) = \mathbf{A}_2\mathbf{x}_{2p}(k-1) + \mathbf{k}_{2p}(k)(\mathbf{u}_p(k) - \mathbf{H}_2\mathbf{A}_2\mathbf{x}_{2p}(k-1)) \tag{14}$$

where

$$\mathbf{A}_2 = \begin{bmatrix} \mathbf{I} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I} & \mathbf{I} \\ \mathbf{0} & \mathbf{0} & \mathbf{I} \end{bmatrix} \quad \text{and} \quad \mathbf{H}_2 = \begin{bmatrix} \mathbf{I} & \mathbf{I} & \mathbf{0} \end{bmatrix}. \tag{15}$$

Similarly as above, gain and the covariance matrix updates for $p = 0, 1, \ldots, P-1$, are obtained as

$$\begin{aligned} \mathbf{P}_{2p}(k|k-1) &= \mathbf{A}_2 \mathbf{P}_{2p}(k-1)\mathbf{A}_2^T + \mathbf{Q}_{2p} && (16) \\ \mathbf{k}_{2p}(k) &= \mathbf{P}_{2p}(k|k-1)\mathbf{H}_2^T(\mathbf{H}_2\mathbf{P}_{2p}(k|k-1)\mathbf{H}_2^T + \mathbf{R}_p)^{-1} && (17) \\ \mathbf{P}_{2p}(k) &= (\mathbf{I} - \mathbf{k}_{2p}(k)\mathbf{H}_2)\mathbf{P}_{2p}(k|k-1). && (18) \end{aligned}$$

The process noise covariance matrix $\mathbf{Q}_{2p}$ is a $3m \times 3m$ matrix defined as

$$\mathbf{Q}_{2p} = \begin{bmatrix} \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \sigma_{v_{2p}}^2 \mathbf{I} \end{bmatrix}. \tag{19}$$

The augmented state is initialized at the spatial position $k = k_0$ by setting the bias to zero and the error covariance matrix $\mathbf{P}_{2p}(k_0)$ to

$$\mathbf{P}_{2p}(k_0) = \begin{bmatrix} \mathbf{P}_{1p}(k_0 - 1) & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \end{bmatrix}. \tag{20}$$

3 Target Detection

While operating in the quiescent state the algorithm uses a χ^2 test based on the measurement prediction error or innovation $\nu_p(k)$, to detect the position of a possible target. In particular, it is expected that the presence of the target return manifests itself as a "large" innovation. Under the hypothesis H_0 it is assumed that the GPR trace $u(n = 0, \ldots, N-1, k)$ contains only the ground return $s^b(n = 0, \ldots, N-1, k)$ plus noise. The alternative hypothesis H_1 is that the target signal $s^t(n = 0, \ldots, N-1, k)$ is also present. For each of the P trace sections of length m, $p = 0, 1, \ldots, P-1$, the measurement prediction error $\nu_p(k)$ is computed as

$$\nu_p(k) = \mathbf{u}_p(k) - \mathbf{u}_p(k|k-1) \tag{21}$$

where

$$\mathbf{u}_p(k|k-1) = \mathbf{H}_1 \mathbf{A}_1 \mathbf{x}_{1p}(k-1) \tag{22}$$

is the measurement prediction. The measurement prediction covariance matrix is updated as

$$\mathbf{S}_p(k) = \mathbf{H}_1 \mathbf{P}_{1p}(k|k-1)\mathbf{H}_1^T + \mathbf{R}_p \tag{23}$$

and used to compute the normalized innovation squared (NIS)

$$\epsilon_p(k) = \nu_p(k)^T \mathbf{S}_p(k)^{-1} \nu_p(k). \tag{24}$$

Under the hypothesis H_0 the variables $\epsilon_p(k),\ p = 0, 1, \ldots, P-1$, are χ^2 distributed with m degrees of freedom. Each of the P trace sections is, then, tested separately using the χ^2 test with the significance level α, so that

$$Pr(\epsilon_p(k) \geq \chi^2_{m,\alpha}) = \alpha. \tag{25}$$

In the case when H_0 is rejected for at least K_0 of the total of P sections, the hypothesis H_0 for the whole trace is rejected and the alternative hypothesis H_1 is accepted. To make the final decision that the target is present, and to change to the augmented state model, the hypothesis H_0 needs to be rejected for at least K_1 consecutively measured GPR traces. After the target detection is declared at the spatial position k, the spatial position at which the augmented state is initialized, k_0, and which is assumed to correspond to the target onset, is determined as $k_0 = k - K_1 - K_\tau$. Here, K_0, K_1 and K_τ are suitably chosen constants. If $K_\tau = 0$, k_0 equals to the spatial position where detection first occurred. If we set $K_\tau > 0$ we assume that the target started before it was first detected.

It is desirable that the augmented state model stays active until the end of the section of GPR traces that contains the target return is detected, when the algorithm should switch back to the quiescent state model. However, the above target detection technique determines the beginning of the target section in the data and a similar approach cannot be devised to define the end of this segment as easily. One solution is to run the proposed algorithm over the target in two opposite directions in order to define the position and the width of the target segment. For simplicity, in this report we apply the algorithm in one direction only and assume that the width of the target segment is constant and known in advance. This assumption is reasonable when the size of the target and the velocity of the antenna are known.

Though here we used NIS for the detection statistic, we note that the detection statistic can also be computed as a moving sum of NIS over the sliding window of length s,

$$\epsilon_p^s(k) = \sum_{j=k-s+1}^{k} \epsilon_p(j). \tag{26}$$

The variable $\epsilon_p^s(k)$ is χ^2 distributed with sm degrees of freedom. The detection statistic defined as in (26) is suitable for noisier backgrounds.

4 Background Adaptation

The GPR background signal is measured as the average over a volume of the ground and its statistics can be assumed to have slow spatial variation. To enable our algorithm to adapt to such variations we use an approach motivated by the continuous noise level (CNL) adjustment technique presented in Bar-Shalom and Li [1]. In particular, the process noise covariance matrix, $Q_{1p}(k)$, that characterizes the background is finely tuned at each spatial position k by multiplying it by a scaling factor $\phi_p(k)$,

$$Q_{1p}(k) = \phi_p(k) Q_{1p}(k-1). \tag{27}$$

This is done for each $p = 0, 1, \ldots, P-1$ separately. At each spatial position k the value of the scaling factor $\phi_p(k)$ is determined by comparing NIS $\epsilon_p(k)$ to a set of thresholds.

These thresholds, denoted as ϵ_1, ϵ_{2_L} and ϵ_{2_H}, are defined so as to satisfy the following equations

$$\begin{aligned} Pr(\epsilon_p(k) < \epsilon_1) &= 1 - \eta_1 && (28)\\ Pr(\epsilon_p(k) < \epsilon_{2_L}) &= 1 - \eta_{2_L} && (29)\\ Pr(\epsilon_p(k) < \epsilon_{2_H}) &= 1 - \eta_{2_H} && (30) \end{aligned}$$

where $\eta_1 > \eta_{2_L} > \eta_{2_H} > \alpha$ and $Pr(\cdot)$ is χ^2 distribution with m degrees of freedom. Ideally, under the background-only assumption, we wish to define the process noise covariance matrix $Q_{1p}(k)$ so that $\epsilon_1 \leq \epsilon_p(k) < \epsilon_{2_L}$, in which case the scaling factor is set to $\phi_p(k) = 1$. If $\epsilon_p(k) < \epsilon_1$, the process noise level is too high and needs to be lowered. We then set $\phi_p(k) = \phi_1$, where $\phi_1 < 1$. Otherwise, if $\epsilon_{2_L} \leq \epsilon_p(k) < \epsilon_{2_H}$, the process noise covariance matrix is increased by setting the scaling factor to $\phi_p(k) = \phi_2$, where $\phi_2 > 1$. In the case when $\epsilon_{2_H} \leq \epsilon_p(k) < \chi^2_{m,\alpha}$ we are not sure weather our background-only assumption is still valid so the process noise level is left unaltered, and $\phi_p(k) = 1$. The same is done for $\epsilon_p(k) \geq \chi^2_{m,\alpha}$. The constants ϕ_1 and ϕ_2 are chosen to be close to 1 and, *i.e.*, $\phi_1 = 0.98$ and $\phi_2 = 1.02$. The decision procedure for setting the value of the scaling factors $\phi_p(k)$ at each spatial position k for which the algorithm operates using the quiescent state model and for $p = 0, 1, \ldots, P-1$, is summarized as follows (see also Figure 1):

$$\begin{aligned} &\textit{step 1:}\ \textbf{set}\quad p = 0 && (31)\\ &\textit{step 2:}\ \textbf{if}\ \epsilon_p(k) < \epsilon_1\ \textbf{set}\ \phi_p(k) = \phi_1\ \textbf{goto}\ \textit{step 3}\\ &\qquad \textbf{if}\ \epsilon_{2_L} \leq \epsilon_p(k) < \epsilon_{2_H}\ \textbf{set}\ \phi_p(k) = \phi_2\ \textbf{goto}\ \textit{step 3}\\ &\qquad \textbf{if}\ \epsilon_1 \leq \epsilon_p(k) < \epsilon_{2_L}\ \textbf{or}\ \epsilon_p(k) \geq \chi^2_{m,\alpha}\ \textbf{set}\ \phi_p(k) = 1\\ &\textit{step 3:}\ \textbf{if}\ p < P\ \textbf{set}\ p = p + 1\ \textbf{goto}\ \textit{step 2} && (32) \end{aligned}$$

5 Simulation Results and Discussion

The Kalman filter-based technique described in Sections 2-4 has been tested using several minelike targets buried in different soils. The targets were surrogate anti-personnel landmines, modelled after a number of anti-personnel blast mines with non-metallic casings [7], and poly-vinyl chloride (PVC) and stainless steel cylinders of different sizes. The surrogate landmines are made of a plastic pipe filled with paraffin wax and small metal parts. The data was collected by means of an FR-127-MCSB impulse GPR developed by CSIRO [6]. The system used a bistatic bow-tie antenna to transmit pulses with 1.4 GHz center frequency and the bandwidth of 1.0 GHz, and collected 127 soundings composed of 512 samples of 12 bit accuracy per second. The length of each trace was 12 ns. To compensate for the ground attenuation and signal spreading the data was taken using the dynamic gain slope of 20 dB. In the process of measurement the antenna was suspended from a track along which it was driven by a stepper motor at constant velocity. More information about the measurement process and conditions can be found in [3].

The proposed technique worked well and was found promising for detecting weak targets. One such example is shown in Figure 2. Figure 2 (a) shows the original GPR plot that contains two targets, the surrogate landmine ST-AP(1) [7] and a PVC cylinder, buried in dry sand at the depth of approximately 1 cm. The dimensions of the targets

are: ST-AP(1): diameter 5.2 cm and height 4.2 cm; PVC cylinder: diameter of 10 cm and height 5 cm. The target-return component of the GPR signal estimated by the proposed algorithm is shown in Figure 2 (b).

Since the individual GPR traces were oversampled in the process of measurement, each of them was decimated by factor 2 prior to the processing. The parameters of the algorithm used to obtain the results in Figure 2 were: the width of the horizontal strips of GPR data processed by one Kalman filter $m = 32$ and the number of such horizontal strips $P = 8$. The significance level for the χ^2 test was $\alpha = 10^{-5}$. Other parameters used in the detection procedure were $K_0 = 1$, $K_1 = 5$ and $K_\tau = 5$, and for the background adaptation $\eta_1 = 0.99$, $\eta_{2_L} = 0.4$, $\eta_{2_H} = 5\alpha$. For all $P = 8$ trace sections the variances of the components of the measurement noise vectors $\mathbf{w}_p$ were identical and equal to σ_w which was estimated off line, similarly as the variances of the components of the process noise vectors in (6). Since the intention was to detect shallowly buried targets, the target detection using χ^2 hypothesis testing was performed only for the top 6 horizontal data strips where the specular return from the targets was expected to be maximum. The more accurate detection results were obtained for the larger values of the parameter m. The drawback was that the computational complexity increased with the size of the matrices used in the algorithm. In our experiments $m = 32$ has been found to enable very accurate target detection with the acceptable computational complexity. The program is implemented using Matlab Numeric Computation and Visualisation Software and is listed in Appendix A. The flow chart of the algorithm is shown in Figure 3.

Figure 4 (a) shows a row from the data in Figure 2 (a), which represents the signal recorded at one particular depth and at consecutive spatial positions (solid line). The corresponding background signal estimated using the Kalman filter-based approach is also shown (dashed line). Figure 4 (b) shows the estimated target signal. The augmented state model was activated over the sections of the signal between the vertical lines, as indicated in the figure. It can be seen that the background follows the received signal at the spatial positions where the target signal is zero, that is, when the quiescent state model is used. At the spatial positions where the target signal is present, *i.e.*, when the augmented state model is active, the background signal stays at the level estimated before the detection.

For comparison, Figure 5 shows the data in Figure 2 (a) processed by background subtraction, where the background signal $b(n)$ is estimated as the mean of the entire data ensemble in Figure 2 (a) (*i.e.*, $b(n) = \sum_{k=0}^{M-1} u_k(n)$, $n = 0, 1, \ldots, N$, and M is the overall number of traces in the ensemble) and subtracted from each trace in the ensemble. In Figure 5 it can be seen that, using this approach, not all clutter has been removed from the data.

6 Conclusions and Future Work

The signatures of shallowly buried targets measured using Ground Penetrating Radar are usually obscured by the return from the air-soil interface. In this report a Kalman filter-based approach has been used to obtain the estimate of this background signal and to separate it from the target return. In the absence of the target the filter operates using a quiescent state model in which it computes the background estimate. When the

target is detected, new state components are added to allow for the change of the signal corresponding to the target return. The augmented state model is used until it reverts to the quiescent model by another decision.

The magnitude of the background signal at one particular depth, and for incrementally updated spatial positions, was modelled as a random walk. The noisy measurements of the background signal were represented using a state space form and a set of Kalman filters was used to obtain the recursive state estimation. At the spatial positions where a target was detected the new state component modelled as the stochastic bias was added. This component was used to compute the estimate of the unknown target signal.

To detect the changes in the signal that are related to the presence of the target a statistic based on the measurement innovation is used in conjunction with an appropriate statistical hypothesis testing procedure.

The proposed algorithm was tested using the data containing several minelike targets and have shown promise for processing GPR data with weak shallow target responses.

The future work will involve using a more elaborate Multiple Model (MM) Kalman filter approach [1]. The assumption of the MM method is that the signal obeys either of the two possible models (*i.e.*, either the target return is present in the signal or not, similarly as described in this report). It computes the probability that each of the models is active at one particular spatial position using a Bayesian approach and can incorporate Markovian assumption. It is expected that more accurate estimation of both the background and the target signal can be obtained using this method. It will also include extending the approach presented in [4].

Acknowledgments

The author is wishes to thank Dr. Ian Chant of DSTO for his encouragement and valuable comments.

References

1. Y. Bar-Shalom and X.-R. Li. *Estimation and tracking: principles, techniques and software.* Artech House, Norwood, MA 020062, 1993.

2. C. Bruschini, B. Gros, F. Guerne, P.-Y. Piece, and O. Carmona. Ground penetrating radar and imaging metal detector for antipersonnel mine detection. *J. Appl. Geophys.*, 40:59–71, 1998.

3. D. Carevic, D. Lee, L. Clonan, and I. Chant. Ground Penetrating Radar measurement series February/March 1998. Internal Divisional Report, Surveillance Systems Division, Defence Science and Technology Organisation, Australia (under review).

4. I. Chant, J. Washl, and R. Bird. Developement of Ground Penetrating Radar as a landmine detector. Technical Report DSTO-TR-0653, Defence Science and Technology Organisation, Australia, 1998.

5. D. J. Daniels. *Surface penetrating radar.* Radar, sonar, navigation and avionics series 6. The Institution of Electrical Engineers, London, UK, 1996.

6. W. Murray, C. J. Williams, and J. T. A. Pollock. A high resolution radar for mine detection. In *Proc. EUREL Int. Conf., EICC*, pages 143–147, Edinburgh, UK, 1996.

7. B. C. Y. Wong, I. Chant, G. N. Crisp, K. Kappra, K. Strugess, A. Rye, and K. Sherbondy. Suggested soil characterisation techniques and surrogate targets for ultra-wideband radar mine detection experiments. In *Proc. SPIE AeroSense*, volume 3079, pages 555–567, Orlando, USA, 1997.

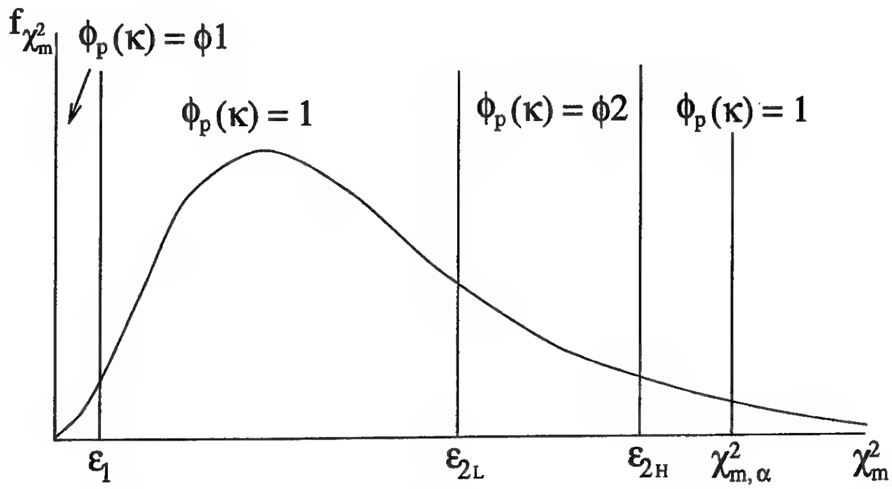
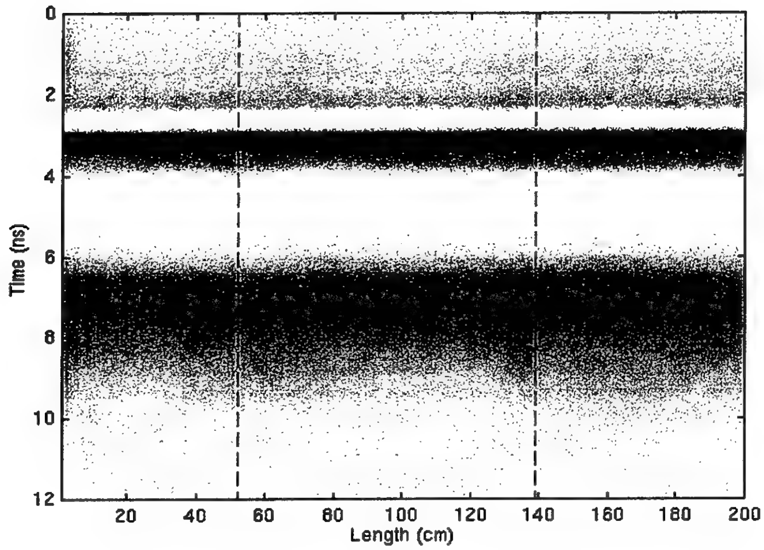
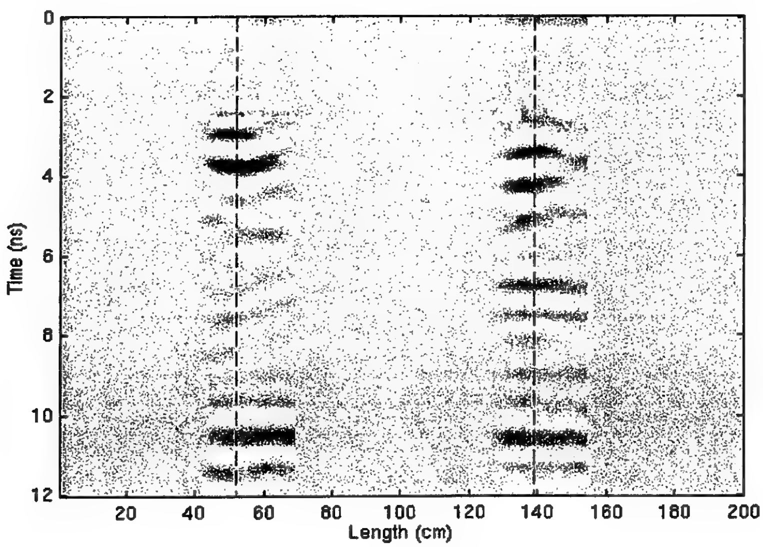


Figure 1: Thresholds ϵ_1, ϵ_{2_L}, ϵ_{2_H} and $\chi^2_{m,\alpha}$ and the corresponding settings of the scaling factors $\phi_p(k)$. Function $f_{\chi^2_m}$ is a χ^2 probability density function.



(a)



(b)

Figure 2: (a) The original GPR data with the surrogate landmine ST-AP(1) (left) and the PVC cylinder (right) buried in dry sand at the depth of 1 cm; (b) the target-return component of the GPR signal estimated by the proposed algorithm. The positions of the targets are indicated.

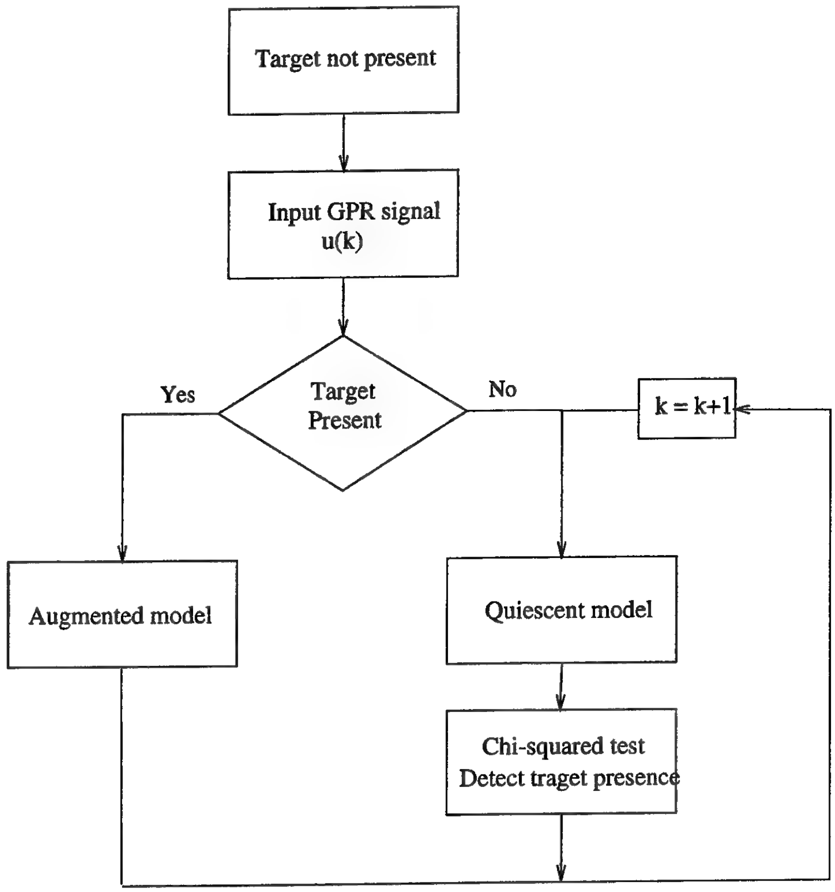


Figure 3: Flow chart of the algorithm.

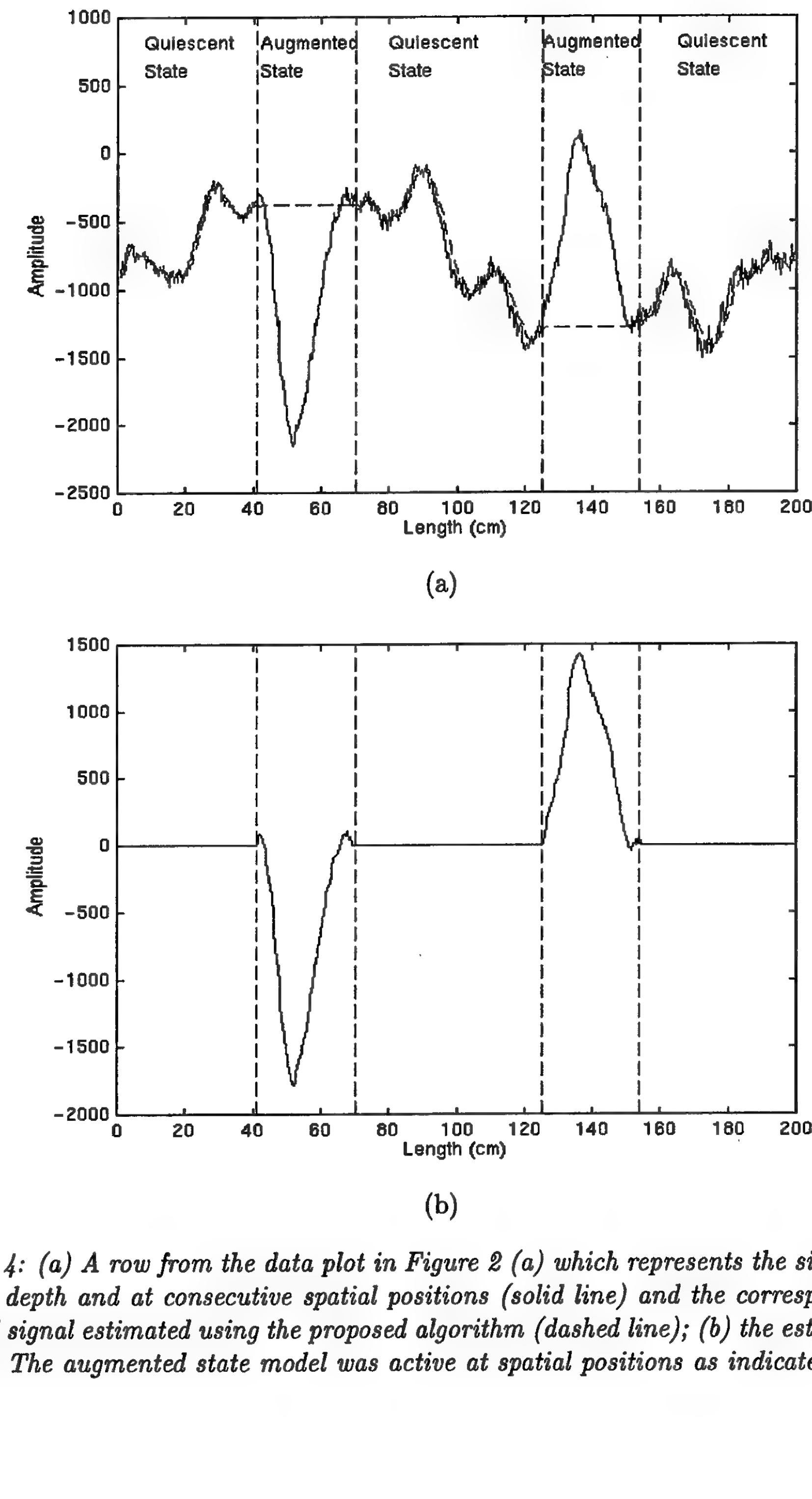


Figure 4: (a) A row from the data plot in Figure 2 (a) which represents the signal recorded at one depth and at consecutive spatial positions (solid line) and the corresponding background signal estimated using the proposed algorithm (dashed line); (b) the estimated target signal. The augmented state model was active at spatial positions as indicated.

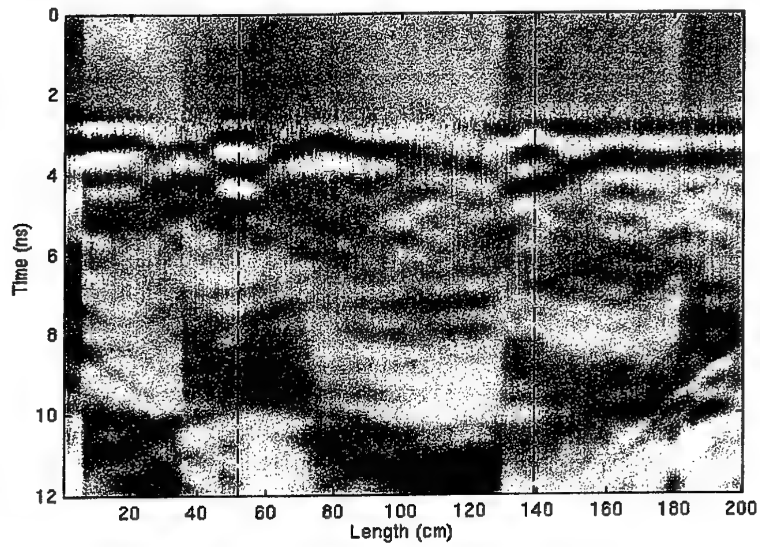


Figure 5: Background-subtracted data in Figure 2 (a), where the background signal is estimated as the mean of the entire ensemble of GPR signals and subtracted from each signal in the ensemble.

Appendix A
Program Listing

```
%*************************************************************************
%
% Function:    [M,M1,B1]=smooth_rw8(D,dim);
%
% This function applies Kalman filtering based on the variable
% state dimension method as expalined in thie report.
%
% Input:       D two-dimensional plot of GPR data
%              dim - width of data strips processed by one Kaman filter
%
% Output:      M  - estimated background signal
%              M1 - estimated target signal
%              B1 - estimated bias
%
% Author:      Dragana Carevic
%              Surveillance Systems Division, DSTO
%
% Date:        18/11/1998
%
%*************************************************************************


           function [M,M1,B1]=smooth_rw8(D,dim);


% Filter out the low-pass component of the signal
qmf=MakeONFilter('Coiflet',1);
[X,Y]=size(D);N=4;k=1; step=4;
%disp([' Step = ',num2str(step)]);

for i = 1:step:Y-step+1
  d=D(:,i);
  d=decimate(d,2,'fir');
  %d = DownDyadLo(d',qmf)';
  wave_coef = FWT_PO(d,N,qmf);
  wave_coef (1:(2^N)) = zeros(size(wave_coef (1:(2^N))));
  dfilt(:,k)= IWT_PO(wave_coef,N,qmf);
  k=k+1;
end;
```

```
numChsqAverage = 1;
chisqPrev = zeros(1,numChsqAverage);
anythingDetected = 0; numLess = 0;
Detection = 0; Thres = -5;
detected=0; detectedRequired=5;
LookAhead = 60; % distance to be looked at in detection
Num = ceil(LookAhead/step) - 1;
NumDetectedTraces = 0; NumBkgTraces = 0;
PrevDetection = 1;

v=40*step;  % std of the measurement noise (cov matrix R)
w0=20*step;  % std of the process noise (for the background) (cov matrix Q)

[XF,YF]=size(dfilt);

m = fix(XF/dim); % number of strips to be processed
Z = zeros(dim,dim); % zero matrix of size dim x dim
II = eye(dim);  % identity matrix of size dim x dim
H = eye(dim);
A = eye(dim);
R = v.^2*eye(dim);  % measurement covariance matrix dim*dim

for i = 1:m
  Q(i,:,:) = w0.^2*eye(dim); % process covariance matrix dim*dim

  P(i,:,:) = zeros(dim,dim);%eye(dim)*5000^2;
              % initialize error covariance matrices for m strips
              % of dimensions m x dim x dim
  K(i,:,:) = zeros(dim,dim);
              % initialize gain matrix for m strips m x dim x dim
end;


M(:,1) = dfilt(:,1);
            % initialize vectors M(:,i) to values defined in dfilt(:,1)
            % M corresponds to the background
M1(1:XF,1) = zeros(XF,1);
            % initialize vectors M1(:,i) to zero
            % M1 corresponds to the signal
B1(1:XF,1) = zeros(XF,1);
            % initialize vector B1(:,1) to zero.
            % B1 corresponds to the signal
j = 2;
while j < YF-1

     PrevDetectionInThisTrace=0;
```

```
disp([' Trace = ',num2str(j)]);
disp([' NumDetectedTraces = ',num2str(NumDetectedTraces)]);
disp([' NumBkgTraces = ',num2str(NumBkgTraces)]);
disp([' PrevDetection = ',num2str(PrevDetection)]);
disp([' PrevDetectionInThisTrace = ',num2str(PrevDetectionInThisTrace)]);
if Detection == 0

NumBkgTraces = NumBkgTraces +1;
if NumBkgTraces > 200/step
   PrevDetection=0;
end;

for i = 1:m        % for the m-th strip at column j

   s=[M(dim*(i-1)+1:dim*i,j-1)']';
                             % this is previous state vector
                             % based on which we are making
                             % current state prediction

   % PREDICTION
   sp = A*s;  % this is current state prediction
   PP(:,:)=P(i,:,:); QQ (:,:) = Q(i,:,:);
   PP=A*PP*A'+ QQ; % prediction error covariance matrix
   mp = H*sp;  % measurement prediction
   S = H*PP*H'+R; % measurement prediction covariance matrix

   % CHI SQUARED TEST FOR TARGET DETECTION
   for l = 1:1

     error = dfilt(dim*(i-1)+1:dim*i,j+1) - mp;
                                  % measurement prediction error

     chisq = error'*inv(S)*error;
     for wtq=1:numChsqAverage-1
      chisqPrev(wtq)=chisqPrev(wtq+1);
     end;
     chisqPrev(numChsqAverage)=chisq;
     chisq=sum(chisqPrev);
              % chi-square variable of dim degrees of freedom
              % mean previously computed numChsqAverage values

     Prob(i,j)=1-chi2cdf(chisq,dim*numChsqAverage) ;
     %disp(['Meras. innovation : Prob = ',num2str((Prob(i,j)))]);

     if j>fix(200/step) &  (Prob(i,j)) <= 10^Thres & i< m/2 & ...
         PrevDetection == 0 & PrevDetectionInThisTrace == 0
```

```
disp(['DETECTION at strip = ',num2str(i)]);
disp(['Prob = ',num2str((Prob(i,j)))]);

if detected ~= 0 & detectedTrace(detected) == j
   break;
end;

anythingDetected = 1;
PrevDetectionInThisTrace = 1;
if detected==0
        % if this is first detected trace
        % initialize new detection

  detectedTrace(1)=j;
  detected = 1;

else % check if there are previous consecutive traces

  if detectedTrace(detected)+1 ~= j
              % if not, reset variable detected to zero

       detected = 1;
       detectedTrace(1)=j; % initialize new detection

  else     % if the traces are consequtive increment
           % variable detected and check if there is
           % detectedRequired number of them

            detected = detected +1;
            detectedTrace(detected)=j;


  end;
end;

if detected == detectedRequired
       Detection =1;
       DetectionTrace=j-1;
       j=j-(detectedRequired+9+2*numChsqAverage);
end;

disp(['detected = ',num2str(detected)]);

% If detection occur switch to other (compund) model
% In particular break out of this loop and use j-1-th
% estimate as the initial value for the new model

break;
```

```
          end;
        end;

        if Detection == 1 break; end;

       % MEASUREMENT UPDATE
       K = PP*H'/(H*PP*H'+R);
       s = sp + K*(dfilt(dim*(i-1)+1:dim*i,j) - H*sp);
                             % update state vector
       P(i,:,:) = PP - K*H*PP;
                             % update error covariance matrix for i-th strip
       M(dim*(i-1)+1:dim*i,j)=s(1:dim);
              % move current m vector to matrix  M(:,i)
       M1(dim*(i-1)+1:dim*i,j)=zeros(dim,1);
       B1(dim*(i-1)+1:dim*i,j)=zeros(dim,1);
              % since no detection occured, B1 and M1 are zero

       % BACKGROUND ADAPTATION
       if min(Prob(i,j)) > 0.99 & anythingDetected == 0
         QQ = 0.98 *QQ;
       end;

       if min(Prob(i,j)) < 0.4 & anythingDetected == 0 & ...
         min(Prob(i,j))  >   5*10^Thres

         numLess = numLess +1;
         if numLess >= 1
             QQ = 1.02 * QQ;
         end;
       else numLess =0;
       Q(i,:,:)=QQ;
     end;

     anythingDetected = 0;

     if Detection == 0
         j=j+1 ;
     end;
     end % if Detection == 0

     if Detection == 1

        if PrevDetection == 0

          % Initialisation of parameters for compond model
          w1 = (70/5)*step;
```

```
      III = eye(3*dim);
      I = eye(dim);
      H1 = [I I Z];
      A1 = [I Z Z; Z I I; Z Z I];
      Q1 = [Z Z Z;Z Z Z; Z Z w1^2*I];

      % Initialise new values for P1 and K1
      % Use old values P and K for the background
      for i = 1 :m
        PP(:,:)=P(i,:,:);
        P1(i,:,:) = [PP Z Z;Z Z Z;Z Z Z];
      end;
      PrevDetection = 1;

    end; %  if PrevDetection == 0

    NumDetectedTraces = NumDetectedTraces +1;

    for i = 1:m

        s1 = [M(dim*(i-1)+1:dim*i,j-1)' M1(dim*(i-1)+1:dim*i,j-1)' ...
                                          B1(dim*(i-1)+1:dim*i,j-1)']';

        % PREDICTION STEP
        sp1 = A1*s1;
        PP1(:,:)=P1(i,:,:);
        PP1 = A1*PP1*A1'+Q1;

        % MEASUREMENT UPDATE
        K1 = PP1*H1'/(H1*PP1*H1'+R);
        s1 = sp1 + K1*(dfilt(dim*(i-1)+1:dim*i,j) - H1*sp1);
                      % update state vector
        P1(i,:,:) = PP1 - K1*H1*PP1;
                     % update error covariance matrix for the i-th strip
        M(dim*(i-1)+1:dim*i,j) = s1(1:dim);
        M1(dim*(i-1)+1:dim*i,j) = s1(dim+1:2*dim);
        B1(dim*(i-1)+1:dim*i,j) = s1(2*dim+1:3*dim);

     end; % for i=1:m

     Prob(:,j)=Prob1(:,j);

     j=j+1;

     if NumDetectedTraces  > 300/step
         detected   = 0;
         Detection = 0;
```

```
        NumBkgTraces = 0;
        NumDetectedTraces =0;
    end;
  end;  % if Detection == 1
end;
```

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A Kalman Filter-based Approach to Target Detection and Target Background Separation in Ground Penetrating Radar

Dragana Carevic

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4. AUTHOR(S) Dragana Carevic	5. CORPORATE AUTHOR Aeronautical and Maritime Research Laboratory PO Box 4331 Melbourne Vic 3001 Australia

6a. DSTO NUMBER	6b. AR NUMBER	6c. TYPE OF REPORT	7. DOCUMENT DATE
DSTO-TR-0853	AR-011-042	Technical Report	August 1999

8. FILE NUMBER	9. TASK NUMBER	10. TASK SPONSOR	11. NO. OF PAGES	12. NO. OF REFERENCES
B9505-17-91	ARM98/007	DGLD	21	7

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Land mine detection, Ground penetrating radar, Kalman filtering, Ground clutter, Target discrimination

19. ABSTRACT

The returns from shallowly buried targets measured using Ground Penetrating Radar (GPR) are typically obscured by a strong background signal comprised of the reflections from the air-soil interface. A Kalman filter-based approach is proposed to estimate this background signal and to separate it from the target return. In the absence of the target the filter operates using a "quiescent state model" in which it computes the background estimate. A statistic based on measurement innovation is applied to detect the target position. Upon detection the state is augmented by a new component which allows for the change of the signal corresponding to the presence of the target return. The augmented state model is used until it is reverted to the quiescent model by another decision.